ROBUSTNESS OF FREQUENCY DIVISION TECHNIQUE IN A SIMULTANEOUS AND PROPORTIONAL MYOELECTRIC CONTROL SCHEME

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ABSTRACT

It is important for myoelectric control schemes to be robust to various non-stationarities in electromyography (EMG) signal such as unintended activations and contraction level variations. In order to address this limitation, the present study compared performance measures of two EMG processing pipelines with two filtering techniques: frequency division technique (FDT) and standard bandpass processing (Bandpass) in a simultaneous and proportional myoelectric control (SPEC) scheme for two contraction levels (medium and high). Twenty able-bodied participants (14 males and 6 females, age 23.4 ± 3.0) performed wrist movements (flexion/extension, rotations and combined movements) in two degrees-of freedom (DOF) virtual tasks. FDT had a mean completion rate (CR) of 95.33%, which was significantly higher than the SPB technique with a CR of 64.08% ($p<0.001$). FDT method performed significantly better in all other performance indices in at least one movement type. Furthermore, there was no significant difference in the performance of FDT between medium and high contraction levels, while there were such differences for bandpass filtering. This study showed that FDT is advantageous in regression based online myoelectric control as it generates a more accurate, robust and contraction level invariant scheme for performing prosthetic hand movements. This study is the first to use frequency-based features with a SPEC scheme and shows promise for more intuitive prosthetic devices.

INTRODUCTION

Myoelectric prostheses use EMG signals for performing prosthetic functions. Conventional control of a myoelectric prosthesis involves mapping the amplitude of EMG signals to the desired prosthetic function. Challenges with the direct control scheme such as EMG crosstalk have led to the use of pattern recognition (PR), a machine learning approach that classifies EMG features to activate different prosthetic functions [1]. Currently, the state-of-the-art PR technique uses linear discriminant analysis (LDA) classifiers applied to a set of time domain (TD) features [2]. However, PR techniques only allow control of one DOF at a given time (sequential control) which is contrary to the natural control flow of the neuromuscular system. In order to achieve a more natural hand movement, simultaneous rather than sequential control is more desirable. Recently researchers have explored regression techniques, which allow for simultaneous and proportional control of the prosthesis [3, 4]. It has been found that linear regression (LR) performed superior to PR in an online closed loop setup [4]. The promising results of regression techniques has warranted further research to improve control of current prosthesis.

However, regression and PR techniques demonstrate relatively poor performance in real-world conditions due to the non-stationarities in EMG patterns and the noise introduced from different sources [5]. These variations or the non-stationaries in EMG may be caused by several factors including variations in training muscle contraction levels [6] and activation of an undesired degree of freedom [7, 8] are critical. One filtering approach using a frequency division technique (FDT) was proposed to increase varying contraction levels in PR-based myoelectric control [9], and this approach was demonstrated in a closed-loop online PR experiment [10], where. the control scheme with the FDT filter was found to be robust against varying levels of training contraction and it performed significantly better than the traditional band-pass technique. Further research with the FDT filtering on simultaneous and proportional myoelectric control (SPEC) scheme paired with FDT is warranted to corroborate findings in the PR-based myoelectric control scheme. Therefore, the purpose of this study was to compare the performance of the FDT and the traditional bandpass processing on a linear regression (LR) based online myoelectric control scheme while intact subjects completing virtual tasks. This study also examined the effects of varying training contraction level on the performance of the FDT based myoelectric control scheme to determine its robustness against force variation.

METHODS

Frequency Division Technique (FDT)

The FDT directly calculates the spectral power of various frequency bands of sEMG using discrete Fourier transform (DFT) by dividing the full bandwidth of sEMG signals into L segments. For the ith segment, let $f_{i,1}$ and $f_{i,ni}$ denote the frequency values of the two endpoints. The feature is defined as

$$DFT_i = F\left[\sum_{j=1}^{n_i}\left|X\left(f_{i,j}\right)\right|\right],\ \text{i}=1,2,\ldots L \qquad (1)$$

where, $X(\cdot)$ denotes the magnitude of the FFT spectrum, F denotes a non-linear smoothing function. In the current study, F is the root operator is used with a value of 2/3. The whole frequency band of EMG (20-450 Hz) is subdivided into six (L=6) equi-width frequency bands (20-92, 92-163,163-235,235-307,307-378, and 378-450 Hz) [10].

Protocol

Twenty intact-limbed participants (6 females and 14 males) with a mean age of 23.4±3.0 years participated in the study. The study was approved by the University Research Ethics Board (REB 2018-079). The participants were asked to sit on a chair in an upright position with both of their upper limbs in a resting position. They faced a computer screen, at an approximate distance of 75 cm. Eight equally spaced (19 mm inter electrode distance) bipolar electrodes (Duotrodes, Myontronics, Inc) were placed at approximately 1/3 distal measured from the olecranon process to the styloid process of the ulna to cover the circumference of the forearm. A commercial wireless biosignal amplifier (Trentadue, OT Bioelettronica, Italy), sampled at 1000 Hz, was used to transmit the signals. The dominant forearm was used for the electrode placement.

Feature Extraction and Testing

The surface EMG signals were processed initially using the common averaging method [10]. This was followed by two filtering techniques for two separate analyses, the band-pass filtering and FDT. The Bandpass filtering involved applying a bandpass filter (second order, Butterworth) from 20 Hz to 450 Hz followed the TD feature set extraction [10]. For FDT, the signals from each channel were divided into specific frequency sub-bands. LR was used for the simultaneous and proportional scheme. The outcomes of the regression model were mapped to the virtual task.

The experimental testing session consisted of two phases: 1) calibration phase and 2) control phase. The window size for processing was set to150 ms and the regression models provided an output every 50 ms. The calibration phase involved training a regression model using EMG signals with position labels of the cursor during wrist flexion/extension (DOF1) and hand pronation/supination (DOF2). In the calibration phase, the participants were instructed to follow the position of a cursor on a screen. In the training phase, the subjects performed two contraction levels: the wrist movements at the normal contraction level, *i.e.* 'train-medium', and wrist movements at a strenuous contraction level, *i.e.* 'train-high'.

From the data acquired in the training phase, a LR model were generated for each of the combination of the two contraction levels, *i.e. train-high* and *train-medium* and two filtering techniques: Bandpass, and FDT, resulting in four experimental sets in the control phase: medium-Bandpass, medium-FDT, high-Bandpass and high-FDT. In the subsequent control phase, the participants performed goal-directed tasks using the four LR models in a random order [10]. In each experimental session, 20 targets from each type of task group, termed type I, type II, and type III at

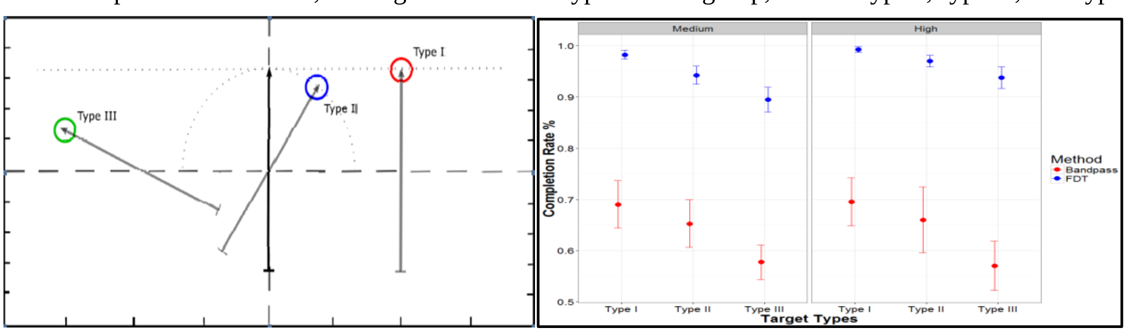

Fig. 1. Left: Goal oriented tasks: type I (flexion/extension DOF only), type II (pronation/supination DOF only) and type III (combination of flexion/extension DOF and pronation/supination DOF). The grey arrow represents the desired position for the completion of the tasks. Right: Mean CR for varying contraction levels (train-medium and train-high) and different processing methods (Bandpass and FDT) for the three types of targets (type I, type II and type III). The error bars represent the standard error.

different locations were provided on the screen (Fig. 2). The targets in type I only require the activation of wrist flexion/extension (DOF1), targets in type II require activation of wrist supination/pronation (DOF2), and targets in type III requires activation of both DOFs. The participants were instructed to place the tip of the arrow in the targets. Instead of sequential articulation of each DOF as in a PR-based control scheme, a simultaneous articulation of both DOFs was used. To measure the performance of these tasks, the performance indices used were: 1) completion rate (CR), the ratio of number of successfully completed task to the total number of tasks in percentage 2) time to reach (T2R), time taken to reach a target in seconds 3) throughput (TP) ratio of task difficulty and task completion time in bits/s and 4) near miss (NM), number of times the cursor enters the target but exits before the completion of 300 ms.

Kruskal Wallis (non-parametric test) was used to determine if the CR of the two filtering techniques were significantly different. Also, for the control participants repeated measures analysis of variance (ANOVA) was used to test for significant differences in mean performance indices (T2R, TP, NM) between FDT and Bandpass from successful trials. With significance resulting from the interaction of main factors the Bonferroni post hoc comparisons were performed to test significant differences in performance measures between FDT and Bandpass. For all the tests, level of significance was $p<0.05$. All the statistical tests were performed using RStudio 1.0. 136 (RStudio, Boston, MA).

RESULTS AND DISCUSSIONS

The mean CR of FDT was 95.33%, which was significantly higher ($p<0.001$) than Bandpass which had a mean CR of 64.08%. This indicates that FDT clearly outperforms the Bandpass. This was supported by the lower variability in CR for FDT compared to Bandpass, indicating less inter-subject variation. In addition, all participants performed equally well with FDT. The same training data was used to train both the processing/feature extraction methods. It was observed for most of the participants that while performing the Bandpass technique, the task arrow was unresponsive in at least one of four LR models. There was also frequent unwanted activation of the non-target DOF. For example, when an individual attempted a wrist extension there was undesired activation of supination as well. On the contrary, the FDT (CR>95%) was robust to unwanted activations and provided a more efficient control scheme. These activations have been briefly discussed by previous regression studies [7, 8], but there has been no detailed analysis on unwanted activations and it is crucial for further studies to research these non-stationarities and mechanisms of addressing them.

The mean T2R was significantly lower ($p<0.001$) for two types of targets (I and III) with FDT than Bandpass (Fig. 3). The mean TP was significantly higher ($p<0.001$) for two types (I and III) with FDT than Bandpass (Fig. 3). The mean NM of only type I target was significantly lower ($p<0.001$) for FDT. The Bandpass performed significantly better ($p<0.001$) than FDT for type II targets. A lower NM implies a more accurate position control. For FDT, the T2R and TP values suggested that the participants performed type I (horizontal only) and III (horizontal and rotation) tasks more easily and at a faster rate. Also, for both techniques, the variability was observed to be consistent for T2R, TP and NM (Fig. 3) suggesting that the participants had equal performance for all target types and across contraction levels. The overall TP and T2R values found in this research were comparable to previous study [10], however the NM was found to be higher. A possible explanation for higher NM is for some participants, the task arrow was unstable at higher pronation and supination angles, thus the participant had to hold it for longer increasing the NM. The mean NM was still low enough to allow real time control and the participants were able to complete tasks.

It was found that there were no significant differences in the mean values of any of the performance measures (CR, TP, T2R, and NM) between the train-medium and the train-high runs for FDT. For CR, the variability was lower

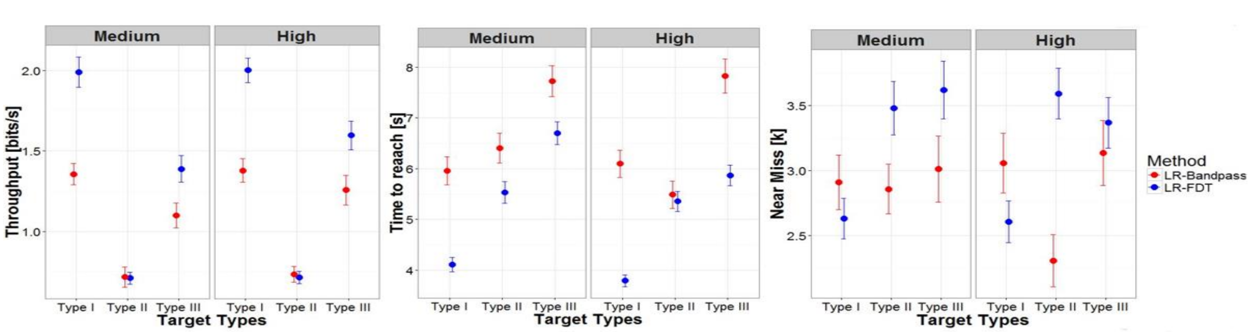

Fig. 3. (From left to right) Mean TP, T2R and NM values for varying contraction levels (train-medium and train-high) and different processing methods (Bandpass and FDT) for the three types of targets (type I, II and III). The error bars represent the standard error.

for FDT than for Bandpass (Fig. 2). For T2R, TP and NM, the variability was found to be consistent across contraction levels for both FDT and Bandpass (Fig. 3). This demonstrates that the performance of FDT is robust to contraction level variations while training. This observation agreed with the findings in [10], which used PR-based methods with FDT and found no difference between performance measures of medium and high contraction level variations [10]. Previously it has also been found out that the power spectrum of some frequency bands are not affected by varying contraction levels [9]. For the testing phase, the participants could perform tasks with any contraction level (medium or high). This finding is very important as the participant's control is independent of the contraction level performed during the training. A freedom of performing movements at a desired contraction level without any performance degradation would be beneficial for the prosthesis users to complete daily living tasks with limited errors.

CONCLUSION

The results from this study suggest that the proposed FDT performs significantly better than the Bandpass method in a LR-based control scheme. Also, the FDT technique is less variant to changing contraction levels. The two processing methods compared in the study used time domain (TD) features and frequency domain (FD) features. Most research studies to date have used the TD feature set. Results found in this study are promising and suggest a need for further research using FD features. The findings of this study directly relate to the robustness of FDT as a myoelectric control scheme which is critical for clinically viable advanced prosthetic control. In another research work (currently under review), the FDT technique demonstrated higher completion rates for individuals with trans-radial amputations compared to the Bandpass. Robustness against these non-stationaries allows users the freedom to operate a prosthesis at their desired contraction levels and prevents erroneous prosthetic functions. Thus, FDT in SPEC control scheme promises greater accuracy, robustness to varying contraction levels, and is more intuitive.

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